

Research Article

Climate Change and the Rise of Obesity

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Abstract

Background: During the past 40-years obesity rates have increased exponentially and the climate has warmed significantly.

Objectives: Obesity does not have easily identifiable causal pathways but there are many multi-modal factors; the contribution of weather and climate to the rise in obesity rates was studied.

Methods: Connections between climate (weather) and obesity was modeled. Both an ecological cross-sectional model typically used in biological studies (Maximum Entropy) and a traditional econometric model (regression and spatial regression techniques) were developed.

Results: Climate variables in all models predicted obesity rates (with and without controlling for socio-economic status and social deprivation). Maximum Entropy models accurately predicted 95.8% of the obesity distribution using maximum temperature (31.5%), insolation (19.6%), surface temperature (17.5%), precipitation (16.5%) and heat index (10.7%). Traditional models predicted 21-39% of the obesity distribution using surface land temperature, heat index and precipitation.

Conclusions: Study results show that climate has the potential to effect obesity etiology. However, this is a pilot study and is limited in scope so results should be considered preliminary.

Could the Changing Climate Affect Obesity?

Background and Objectives Climate Change

In the late 20th century, temperatures in cities have increased

significantly faster as compared to rural areas [1]. Research shows during extreme heat events, both morbidity and mortality increase and correspond to physiologic changes rendering individuals sensitive to the heat [2]. In addition, the climate has also been changing over the same time period [3-5]. As the climate warms, health impacts are predicted to co-occur.

Changes in the frequency and intensity of thermal extremes and extreme weather events (i.e. floods and droughts) directly affect human health [6].

The changing climate could possibly create adaptive pressure selecting for different phenotypes in future generations. As the earth's climate warms, substantial shifts in weather patterns are occurring. Whether it is human industry or a natural phenomenon, the climate has warmed by 2-3°C in the past century [7] and an increase of just 2°C more will shift the climate to a state similar to the Pliocene era [8]. The climate in the Pliocene was much warmer especially at high latitudes. There was less ice at the poles creating a higher sea level, the temperate zone was significantly more arid creating evolutionary pressure for larger grazing animals [9]. The changing modern climate also might create evolutionary pressure to select for different traits in a myriad of species including humans.

Obesity Rates

Obesity rates have climbed over the past forty years [10,11]. The obesity epidemic continues around the world with obesity rates much higher than they were a generation ago. In 2012, 34.9% (95% CI, 32.0%-37.9%) of US adults and 16.9% (95% CI, 14.9%-19.2%) of 2- to 19-year-olds were obese [12] and in Europe greater than 30% of all European children are overweight or obese [13]. In the US, obesity seems to concentrate in geographic areas with lower socioeconomic status. In the South Pacific, Latin America and China, obesity concentrates in areas with higher socioeconomic status [13]. Estimates of geographic obesity rates are limited by the data collection protocol and may severely underestimate obesity rates if self-report data is used [14].

Adaptive Pressure

Human physiology is inseparably interwoven with their environment and a reaction to the changing climate is beginning to manifest because of the high temperatures, and air pollution in many cities [1]. Human metabolism is tied to the link between food procurement, the physical exertion to obtain calories, and eating, the actual caloric intake; choices of what to eat were controlled by environmental conditions. The choice of what to eat for modern humans is also tied to their environment. Eating, physical activity, body metabolism and weight are physiologically regulated together [15]. In modern times, obesity is the response to excess caloric intake exceeding physical exertion. Modern humans are now "embedded in" an environment creating a long-term energy imbalance in favor of obesity [13]. Adaptive responses to a poor or stressful early life environment can change the developmental pathways of the offspring [16]. For example, food shortages during the grandparent or parent's pregnancy can create phenotypes in the ensuing children selecting for obesity when food is plentiful [17].

The cause-and-effect chain from climate change to changing patterns of human health and phenotypes is extremely complex and multifactorial (socioeconomic status, public health infrastructure, access to medical care, nutrition, types of agricultural crops produced, safe water, and sanitation). Genetic mutations can provide a survival advantage as the climate changes, but genetic mutations generally require prolonged, evolutionary time periods to influence the gene pool of a population [18]. Mutations are not reversible or rapidly adaptable as the environmental conditions change; but, epigenetic early life programming may provide a species survival benefit by developing offspring phenotypes adaptable to changing environmental conditions [18]. Epigenetics (phenotype selection) is mediated through environmental exposures raising the possibilities of reciprocal feedback loops between the climate and human health outcomes caused by phenotype expression.

The current paper explores the ecological relationship between climatic factors and current county-level rates for obesity within the continental United States. Our purpose is not to establish a causal relationship between climate and obesity, but to begin a new thread of scientific inquiry based on association linking county-level climate variables to obesity rates.

Objective

To explore the contribution of climate factors to rising obesity rates.

Methods

A species niche model typically used in biological studies (Maximum Entropy) was compared with more traditional econometric models (traditional regression and spatial regression models). The models were used to predict the effects of climate variables on human obesity rates, controlling for measures of socio-economic status and social deprivation. We triangulated methods in order to: 1) validate the results from maximum entropy modeling, and 2) control for socioeconomic variables associated with obesity and possibly climate, since maximum entropy modeling lacks this capacity and 3) test for differing types of spatial dependence to assure the least biased and most efficient estimates of the climate variables in question.

Data

The data used in these analyses includes over 600 variables compiled from a variety of publically available sources. The dependent variable obtained from the CDC interactive Atlas, age adjusted obesity rates from 2009, is used as a continuous variable in the regression based analysis and converted to a binary variable as obesity present/ absent where presence is indicated as a value in the highest quartile. County-level variables concerning socio-economic indicators were obtained from the Area Resource File (2011-2012), GeoLytics, Inc. (East

Brunswick, NJ). GeoLytics bases their estimates on US Census Bureau reports, and county level estimates of residential isolation and income inequality were obtained from the publicly available web site of the Arizona State University GeoDa Center [19]. The variables are: Gini Coefficient measuring income inequality in 2000; Gini Coefficient measuring income inequality in 2010; Unemployment rate for adults aged 18-64, 2010; Percentage households with no vehicle and residing more than one mile from a grocery store, 2008; Percentage households with incomes less than poverty, 2008; Percentage population non-Hispanic Black, 2008; Median household income; Black female headed households with children under 18 years old; White female headed households with children under 18 years old; Percentage white households owner occupied; Percentage black households owner occupied; Percentage white male adults > 21 years old with less than high school education; Percentage white female adults > 21 years old with less than high school education; Percentage black male adults > 21 years old with less than high school education; Percentage black female adults > 21 years old with less than high school education; Percentage black households with more than one person per room; Percentage white households with more than one person per room; Percentage of population living in urban areas; Percentage of women > 18 years old that are divorced; Percentage population foreign born; Percentage of population < 65 years old without health insurance. The climate variables were obtained from the CDC Wonder Environmental Health Module (2000-2009) measuring Surface Land Temperature, Maximum and Minimum Daily Temperatures, Average Daily Temperature and Average Daily Heat Index.

Analysis

Maximum entropy modeling (MaxENT) used six climate variables as predictors of either high or low rates of obesity. Maximum entropy models were used to predict obesity distribution for humans in a manner similar to its typical use for predicting the distribution of species in ecologic analyses [20]. Six climate variables: heat index, minimum & maximum daily temperatures, precipitation, surface land temperature and insolation (solar radiation received over a given area) were used as covariates. Counties with obesity levels in the highest quartile were treated as a "species" and coded as a binary variable with the remaining counties treated as lacking the species. Stated another way, counties with rates of obesity in the highest obesity quartile were coded as one, with the remaining counties coded as zeros. This binary obesity variable was used to train the model. We used obesity rate data from 2000 to train the model to determine the variable contribution to obesity rates in 2009, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly

permuted. The model was re-evaluated on the permuted data, and the resulting drop in training AUC calculated.

Linear regression models with controls for spatial dependence was used to predict climate factors contribution to county level obesity rates. Since obesity data are available as rates and they follow a bell shape curve, linear regression was employed, instead of Poisson regression. The model included three climate factors (surface land temperature, heat index and precipitation) to avoid multi-collinearity with the other climate variables. The model included socio-economic conditions which are potential confounders for the relationship between climate and obesity. While these variables are highly inter-correlated, they served as control variables, recognizing there was multi-collinearity within these variable the individual coefficients and their significance are neither relevant nor interpretable for the study. The socioeconomic variables used were SES Control Variables are: Gini Coefficient measuring income inequality in 2000; Gini Coefficient measuring income inequality in 2010; Unemployment rate for adults aged 18-64, 2010; Percentage households with no vehicle and residing more than one mile from a grocery store, 2008; Percentage households with incomes less than poverty, 2008; Percentage population non-Hispanic Black, 2008; Median household income; Black female headed households with children under 18 years old; White female headed households with children under 18 years old; Percentage white households owner occupied; Percentage black households owner occupied; Percentage white male adults over 21 years old with less than high school education; Percentage white female adults over 21 years old with less than high school education; Percentage black male adults over 21 years old with less than high school education; Percentage black female adults over 21 years old with less than high school education; Percentage black households with more than one person per room; Percentage white households with more than one person per room; Percentage of population living in urban areas; Percentage of women over 18 years old that are divorced; Percentage population foreign born; Percentage of population less than 65 years old without health insurance. The data was obtained either from the CDC open public data at <http://wonder.cdc.gov/welcomeA.html> or The American Census Factfinder at <http://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml>). The climate variables were obtained from the CDC Wonder Environmental Health Module (2000-2009) measuring heat index, minimum & maximum daily temperatures, precipitation, surface land temperature and insolation (solar radiation received over a given area) (the data was obtained from <http://wonder.cdc.gov/EnvironmentalData.html>).

The ecological or spatial nature of the data creates problems for traditional regression analysis [21]. Linear regression assumes independently and identically distributed error terms. A correlation among observations in space, generally referred to as spatial dependence, often causes cross-sectional models to fail because it leads to biased estimates for coefficients and

corresponding standard errors in linear regression [21]. The spatial error model which partitions the error term into a random and spatially dependent component was used to control for the spatial nature of the data; the spatially dependent component was specified with a spatial weights matrix and included on the right-hand side in the final model specification [22].

Results

The obesity distribution was predicted from climate factors (heat index, minimum & maximum daily temperature, precipitation, land surface temperature and insolation) utilizing maximum entropy modeling. The results are displayed in Figures 1 and 2. MaxENT used the climate factors in these counties to predict the obesity distribution. In Figure 1 orange and yellow represent the presence of high obesity rates in individual counties. As the color on the map changes from blue to green and yellow, higher rates of obesity are predicted; the highest rates of obesity predicted are the intense yellows. In Figure 2 orange and yellow represent the absence of obesity in counties and the blues and green signify the presence of obesity. The relative contributions of the climate variables to the MaxENT model predicting county obesity rates are: precipitation (39%), heat index (19.5%), maximum temperature (18.7%) and surface land temperature (12%) totaling 89.2%. These four variables predict obesity distribution 89.2% of the time. Permutation importance changes the picture regarding which variables have the highest impact on prediction of obesity distribution: maximum temperature (31.5%), insolation (19.6%), surface land temperature (17.5%), precipitation (16.5%) and heat index (10.7%). These five variables predict obesity distribution 95.8% of the time. Thus, maximum temperature (31.5%) had the highest importance in predicting obesity distribution. The area under the curve for the prediction (AUC= 0.845) verifying the MaxENT model has good fit (Figures 1 and 2). The model has > 0.90 sensitivity with specificity ranging from 0.35-0.999 when modeling from the training data.

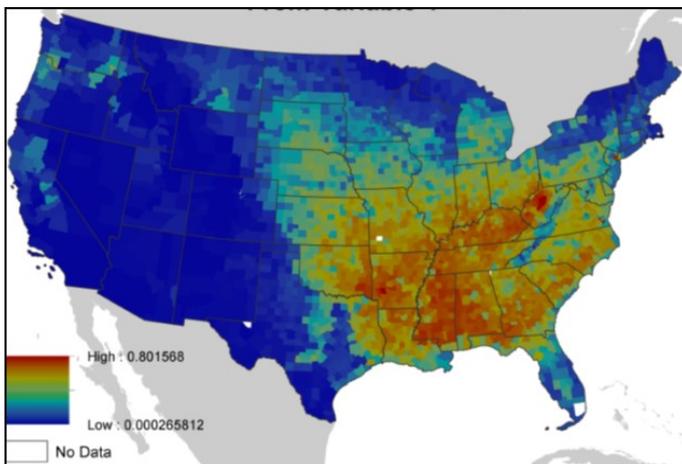


Figure 1. 2009 Prediction of high adult obesity levels by county using climate variables (heat index, minimum & maximum daily tempera-

tures, precipitation, land surface temperature and insolation). The darker orange color indicates high obesity rates.

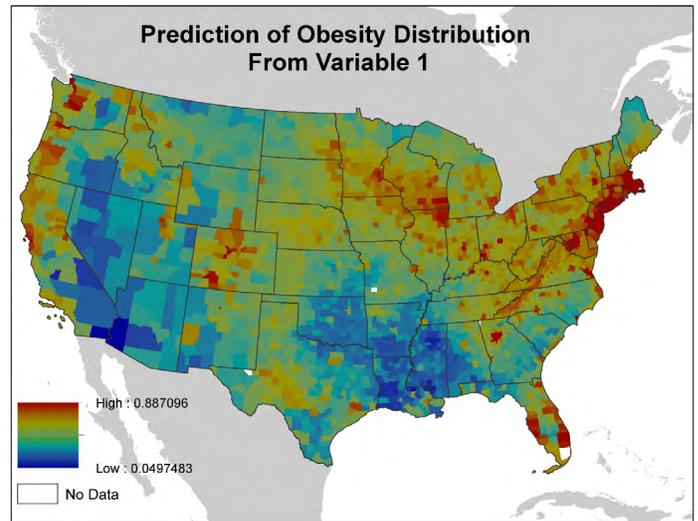


Figure 2. 2009 Prediction of low adult obesity levels by county using climate variables (heat index, minimum & maximum daily temperatures, precipitation, land surface temperature and insolation). The darker orange color indicates low obesity rates.

A linear regression model explains slightly, but significantly, 21.4% of the obesity distribution (Table 1) Adding the SES variables to the linear regression explains 38.5% of the obesity distribution (Table 2). The SES variables (Unemployment Rate, White Female Adults with less than a High School Education, Percent Divorced Females, Percent Foreign Born and Percent older than 65 with No health insurance) mediates the relationship between Precipitation and Heat Index. Despite the mediation, a one unit increase in precipitation rates is still associated with a 0.77% increase in county obesity and a one unit change in Heat Index is associated with a 0.15% increase in obesity within a county. Socioeconomic variables in the model do not affect the climate factors which are still positively and significantly associated with county obesity rates. The spatial error model (Table 3) essentially replicates the traditional linear regression models (Tables 1 and 2). Similar coefficients for climate variables across the differing approaches demonstrate the robustness of these variables toward predicting obesity.

Table 1. Linear Regression with Climate Variables.

	Estimate	Std. Error	t value	Pr(> z)	R ²
Intercept	6.7552	1.0325	6.5428	0.0000*	
Surface Land Temperature	0.0408	0.0095	4.2978	0.0000*	
Heat Index	0.1895	0.0132	14.3540	0.0000*	
Precipitation	1.3499	0.0832	16.2178	0.0000*	
					0.2143

*Significant at 0.001

Table 2. Linear Regression with Climate and SES variables.

	Estimate	Std. Error	T value	Pr(> t)	R ²
Intercept	20.9298	5.9685	3.5067	0.0005*	
Surface Land Temperature	0.0655	0.0109	6.0347	0.0000*	
Heat Index	0.1491	0.0123	12.1682	0.0000*	
Precipitation	0.7675	0.0945	8.1237	0.0000*	
Gini 2000	-0.3600	1.8357	-0.1961	0.8446	
Unemployment Rate	0.7002	0.0366	19.1430	0.0000*	
Percent households no vehicle > 1 mile grocery store	-0.0263	0.0376	-0.6998	0.4841	
Poverty Rate	-0.0271	0.0246	-1.1006	0.2712	
Percent Black	0.0192	0.0061	3.1565	0.0016	
Log of Median Household Income	-1.1376	0.5596	-2.0328	0.0422	
Gini Index	3.7384	1.9251	1.9419	0.0522	
Percent Black Single Parent Households	0.2637	0.2292	1.1503	0.2501	
Percent White Single Parent Households	-0.7764	1.7318	-0.4483	0.6539	
Percent White Owner Occupied House	-0.9001	0.9957	-0.9040	0.3661	
Percent Black Owner Occupied House	-0.3478	0.2115	-1.6442	0.1002	
White Male Adults < HS Education	1.1585	1.9057	0.6079	0.5433	
White Female Adults < HS Education	8.0390	2.1530	3.7339	0.0002*	
Black Male Adults < HS Education	-0.3747	0.3207	-1.1685	0.2427	
Black Female Adults < HS Education	0.0996	0.3304	0.3015	0.7630	
Percent White households with more than one person per room	-0.2713	0.5087	-0.5334	0.5938	
Percent Black households with more than one person per room	-14.4217	6.5680	-2.1958	0.0282	
Percent Urban Pop	-0.0016	0.0034	-0.4645	0.6423	
Percent Divorced Females	-0.2126	0.0340	-6.2464	0.0000*	
Percent Foreign Born	-0.1177	0.0172	-6.8527	0.0000*	
Percent <65 No Hlth Ins	-0.0569	0.0144	-3.9457	0.0001*	
					0.3850

*Significant at 0.001

Table 3. Spatial Error Model with Climate and SES variables.

	Estimate	Std. Error	z value	Pr(> z)
intercept	20.4969	5.9428	3.449	0.0006*
Surface Land Temperature	0.0702	0.0109	6.4298	0.0000*
Heat Index	0.1462	0.0122	12.0022	0.0000*
Precipitation	0.7854	0.0945	8.3132	0.0000*
Gini 2000	-0.5719	1.8274	-0.313	0.7543
Unemployment Rate	0.7119	0.0366	19.4383	0.0000*
Percent households no vehicle > 1 mile grocery store	-0.0275	0.0374	-0.7353	0.4622
Poverty Rate	-0.0262	0.0244	-1.0729	0.2833
Percent Population Black	0.0185	0.006	3.0704	0.0021
Log of Median Household Income	-1.0978	0.5574	-1.9696	0.0489
Gini Index	3.5757	1.9099	1.8722	0.0612
Percent Black Single Parent Households	0.2848	0.2275	1.2519	0.2106
Percent White Single Parent Households	-0.7946	1.7203	-0.4619	0.6441
Percent White Owner Occupied House	-0.9699	0.9889	-0.9808	0.3267
Percent Black Owner Occupied House	-0.307	0.21	-1.4616	0.1438
White Male Adults < HS Education	1.1302	1.8967	0.5959	0.5513
White Female Adults < HS Education	7.7832	2.1417	3.6341	0.0003*
Black Male Adults < HS Education	-0.387	0.3178	-1.2177	0.2233
Black Female Adults < HS Education	0.0895	0.3276	0.2733	0.7846
Percent White households with more than one person per room	-0.2258	0.5052	-0.447	0.6549
Percent Black households with more than one person per room	-13.5235	6.5287	-2.0714	0.0383
Percent Urban	-0.0021	0.0034	-0.6294	0.5291
Percent Divorced Females	-0.2059	0.0339	-6.0746	0.0000*
Percent Foreign Born	-0.1115	0.0172	-6.4734	0.0000*
Percent <65 No Hlth Ins	-0.059	0.0144	-4.0922	0.0000*
spatial autocorrelation parameter	0.098449			
AIC	16320.31			
Log Likelihood	-8133.153			
LR Test	0.0010262			
Wald Test	0.00077167			

*Significant at 0.001

Discussion

A relationship between climate variables and human obesity distribution is apparent when comparing our maps of predicted obesity prevalence to the CDC determined obesity rates [23]. Our study is the first model to use climate variables to predict population obesity distributions. von Hippel and Benson [24]. reported a relationship between obesity and natural factors such as mean summer and winter temperatures; sunlight; and wind speed moderated by physical activity [24]. Our modeling predicted obesity distribution solely from climate factors (heat index, minimum & maximum daily temperatures, precipitation, land surface temperature and insolation), and these relationships persisted after controlling for the potentially confounding effects of socioeconomic variables known to be associated with obesity. Our study design triangulated the significance of associations between climate and obesity similar to recent findings showing human health morbidity and mortality outcomes are related to severe and changing weather patterns [25].

Our findings are also consistent with previous research showing in humans, long-term exposure to cold environments increases brown fat; brown fat burns energy and glucose to make heat and has been postulated to protect individuals against obesity. [26] Conversely, long term exposure to hot environments has been shown to cause heat stress [27, 28]. Our findings suggest where women are most likely to experience heat stress during pregnancy, obesity rates tend to be highest. This is consistent with a hypothesis, heat stress during pregnancy contributes to rising obesity rates. Heat stress causes changes especially in pregnant females creating physiologic changes in their offspring metabolism [29-31]. Stress, including heat stress, increases cortisol levels in pregnant women; cortisol stimulates gluconeogenesis and glycogen synthesis in the liver; both affect circulating glucose concentrations available for mother and fetus [32]. The constant cortisol-exposure associated with stress, even for relatively short periods of time, produces decreased thyroid function, changes the glucose-glycogen metabolism pathways and causes accumulation of abdominal fat [32]. We found high temperature, precipitation and heat all co-occur with obesity. Counties with high heat indices (i.e. have climates that heat stress the population) are also the counties predicted to have and actually have high obesity. As the climate warms, extreme summer heat in parts of the US has exposed large numbers of pregnant women to heat stress [33].

Air conditioning was not prevalent in the South even 20 years ago, exposing the population to the heat extremes [34]. Air conditioning rates throughout most of the United States rose from 1960 on but did not become widely prevalent until the 2000s (and lack of air conditioning persists to the present day in some of the poorest counties) [24]. The spread of air conditioning, especially in the South, rather than general so-

cioeconomic change, in the 1970s explains ~ 60% of the reduction in seasonality of fertility and mortality in the US[34]. In 1960, 88% of the housing units did not have any type of air conditioning and only 2% had central air and 10% had window units (1960 Census <http://www.census.gov/prod/www/decennial.html>). By 2010, 65% of housing units had central air conditioning and another 21% had window units (2010 Census <http://www.census.gov/newsroom/releases/archives/housing/cb10-124.html>). In conjunction with the advent of air conditioning since the 1960s, there has been an increase in the annual number of heat-stress events, particularly in urban and suburban areas [35] (Seiver 1985). Indoor air conditioning did change behaviors with “residents of extreme climates now spend more of their time indoors in temperatures where metabolic rates are rarely elevated and there is ample opportunity for sedentary behavior and snacking [24].”

The pattern of obesity distribution predicted by our model using precipitation, Heat index, Maximum temperature, Surface temperature, Sunlight and Minimum temperature looks very similar to obesity prevalence data collected by the CDC in the same time period. The effect of climate on health outcomes was thought to be moderated by many factors such as socio-demographics and social deprivation, but our models showed obesity prediction by climate was not moderated [36]. Thus, climate change could reverse any health gains achieved by social development. Our study is one of the few studies of the associations between climate and health outcomes conducted across a wide range of geographic regions [6, 36]. The severity of the obesity epidemic will be determined by a myriad of factors and should include climate and non-climatic factors [6]. Both evolutionary adaptation and human behavior will affect the rate of obesity in the coming years.

Limitations

The study has significant methodological limitations, only one year of data (2000) was used to model the effect of climate on obesity rates (in 2009). The only available data and were limited in scope and there are many proposed confounding variables, hence limited variables were analyzed. Nonetheless, future studies with more comprehensive documentation of climate variables and longitudinal in timeframe are needed. Geographic differences in the reliability of the obesity data may also confound the interpretation of geographic variations in the prevalence of obesity [14]. The increase in climate fluctuation in the temperate zone could explain the changing demographics of health in the United States (i.e. the large increase in obesity, hypertension and diabetes).

Conclusions

“Weather has only recently been considered a potentially hazardous exposure that needs to be evaluated in its own right” as to its effects on health [6]. Our data based suggest climate

and environmental factors need to be considered when studying obesity distribution and prevalence. Environmental triggers during development can also affect obesity expression. Within the same geographic area significantly different levels of education, poverty, and other indicators of socio-economic status may be found for different groups. Thus, to understand obesity development: 1) climate exposure, 2) a comprehensive description of environmental factor exposure in the neighborhood and 3) an individual's genetic makeup is needed. "Some climate change scenarios project warming of 4–7°C ... by the end of the 21st century. If this change happens, then the hottest days will exceed present temperatures by a wide margin and increase the number of people who live in conditions that are so extreme [36]." New ecological system approaches are called for to better understand the obesity epidemic so better solutions can be developed.

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